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Employment Duration and Match Quality over the Business Cycle

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In Progress

Abstract

This paper studies the cyclical behavior of employment duration using data from the National Longitudinal Survey of Youth 1979 cohort. We estimate a proportional hazard model with competing risks, distinguishing different types of separations. A higher unemployment rate at the start of an employment relationship increases the probability that the worker quits to take or look for another job, but it decreases the probability that the firm fires the worker. The net effect of these opposing forces on the overall duration of the employment is negative, but small, implying that match quality is weakly pro-cyclical. We also build a simple job-ladder model to interpret our empirical results.

Keywords: Business cycles, employment, quits, firing, match quality, job duration
JEL Classifications: E24, E32, J22, J63, J64.

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1 Introduction

In a frictional labor market, firms and workers may not always be able to find their best match. If the quality of match is not perfect, reallocating workers across firms can improve overall economic efficiency. From a macroeconomic viewpoint, since the degree of frictions in labor market vary over different phases of the business cycle, it is natural to ask whether a better quality match is formed during booms than recessions. We approach this question by analyzing employment duration of workers.

The main idea behind our study is that a worker-firm match with a higher match quality would last longer. If a worker is more productive in a particular firm than another firm, it is more likely that he would be paid better in the former firm, and thus it is less likely to leave that firm. From the firm's perspective, if a worker is more productive than another worker, it is less likely to fire that worker. The advantage of our approach, compared to the alternative approach of directly measuring productivity and wages from matched employer-employee data, is that we can consider a broader concept of match quality that does not show up in output and wages, such as the attachment of a worker to a particular firm or the worker's geographical preferences. To the extent that what we eventually care is the aggregate *welfare*, rather than the *output* itself, this is an advantage rather than a shortcoming.

At the general level, the theoretical predictions about how business cycle affect the formation of match quality is ambiguous. On one hand, the unemployment rate is high during a recession, and job seekers compete for a relatively small number of job openings. Thus the workers are willing to accept a job with a low match quality, perhaps foreseeing that they will look for a better job in future. On the other hand, labor market conditions are favorable for hiring firms during a recession, because there are a relatively small number of hiring firms. Thus the firm is able to wait until finding a worker with a high match quality. As a result, the aggregate labor market conditions at the start of a job have an ambiguous effect on employment duration. In the prototypical Mortensen and Pissarides (1994) model, modified so that the initial match quality is allowed to be stochastic, a high general productivity in boom allows a low-quality match to be formed. If this effect is strong, the average quality of new match tends to be countercyclical. However, the result also depends on how the frequency of job arrival rate changes, and it is also affected by other elements such as on-the-job search. The distribution of match quality draw, which is assumed as acyclical in above scenario, can also be cyclical in reality.

We empirically study the effects of aggregate labor market conditions on employment duration using data from the National Longitudinal Survey of Youth (NLSY) 1979 cohort. We use the Cox (1972) proportional hazard model for job terminations. Our main innovation

is that we estimate the effects of unemployment rate separately for different types of job terminations. First, we separate the separation types by reasons, in particular separations by the workers' quit decision and those ended by the firms' firing decision. Second, we consider the distinction between job-to-job transition and separation into unemployment.¹

Theoretically, we build a standard job-ladder model to study the match quality over the business cycle. The model generated data exhibits a similar pattern as the empirical results. The cyclicity of job-to-job transitions is essential in generating the observed pattern.

The pioneering work by Bowlus (1995) also studies the employment duration over the business cycle. We show that Bowlus' (1995) result, which indicates that the unemployment rate at the start of the job has negative effect on employment duration, is substantially weaker in our dataset which includes longer time series. In macroeconomic literature, her result has been interpreted as an evidence that the match formed during booms is of higher quality,² but in our dataset the result seems more nuanced. The main difference of our study from Bowlus (1995) is that we show that once we look at different types of job terminations separately, we can draw a clearer conclusion on the effect of the business cycle on employment duration. Similarly to Bowlus (1995), a recent paper by Mustre-del-Rio (2014) also finds that a match formed during booms last longer. His methodology is different from ours and he focuses on the contrast between the effect of the unemployment rate at the time of match termination versus the effect of the unemployment rate at the time of match formation.

There is an additional reason why it is important that we separate the types of job terminations. In the estimation of Bowlus (1995) and Mustre-del-Rio (2014), the current unemployment rate is included as an independent variable. However, it is well known that quit is procyclical and layoff is countercyclical (similarly, job-to-job transition is procyclical and the transition from employment to unemployment is countercyclical), and thus the current unemployment rate has an opposite effects on employment duration and can cancel each other out.³ In our estimation, we can estimate the both effects separately.

We find that a high unemployment rate at the start of a job increases the probability that a worker quits his current job, but it reduces the probability that a job spell ends by firm's firing decision. The overall effect of the unemployment rate at the start of a job on employment duration is negative, implying match quality is procyclical. However, this overall effect is small, in contrast to Bowlus (1995). The median duration of a non-union job held by a 29 year-old white male with a high school degree falls from 44 weeks to only 42 weeks

¹In our dataset, there is no distinction between unemployment and not in the labor force. We label all nonemployment as "unemployment" in this paper.

²See, for example, Costain and Reiter (2008).

³Kahn (2008) finds a similar result using a matched employer-employee data set and after controlling for firm fixed effects.

if the unemployment rate at the start of the job is one standard deviation above its sample mean. As is expected, an increase in the current unemployment rate reduces the probability that the job spell end by the worker’s quit decision, but it increases the probability that the firm fires the worker.

When we separate the terminations into job-to-job transition (*EE* transition) and the transition to unemployment (*EU* transition), we find a similar pattern to the distinction between quits and firings. This is as expected, because fired workers tend to move to nonemployment after separation, while quit tends to correspond to job-to-job transition.⁴

The contrasting effect on different types of terminations calls for a theoretical interpretation. To this end, we build a quantitative job-ladder model that features both endogenous separation and on-the-job search. We estimate the model-generated data in the same way as we treat the NLSY data. There, *EE* transitions and *EU* transitions are both separations, and jobs that end up separating quickly are not of high match quality, but there are some differences between different types of separations. The matches that endogenously ends as *EU* transitions are at the bottom of the match quality, that is, of very small match surplus. In contrast, it is possible that the matches that ends in *EE* transitions having a decent match quality—workers quit because they find a job with even higher match quality. More of “very bottom” jobs tends to be created in booms and that is why more jobs that ends up as *EU* transitions are created in booms. In recessions, many jobs created by job-to-job transitions are of lower match quality, because the job-to-job transition itself is slower.

In the next section, we describe the dataset. Section 3 describes the empirical methodology, in particular cause-specific and subhazard regressions. We present the estimation results in Section 4. Section 5 describes the theoretical framework and results. Section 6 concludes.

2 Data description

We use data from the NLSY 1979 cohort in this study. A total of 12,686 individuals that were born between 1957 and 1964 participated in this survey. These individuals were interviewed annually from 1979 through 1994 and biennially thereafter until the survey ended in 2010. The data set we use in this study covers all the survey years.

The survey collects detailed information about each job a respondent holds or previously held. The structure of the survey enables us to create employment histories for all the individuals participating in the survey. We construct the data set for the employment duration analysis by linking each job across different survey years.⁵ We measure the duration of a

⁴See Akerlof, Rose, and Yellen (1989) for a discussion.

⁵We obtain some of the job-specific characteristics, e.g. job start and stop dates, from the Employer

job spell in weeks. Some of the job spells are right-censored due to the finite horizon of the survey and loss of follow-up.

The explanatory variables include personal and job characteristics at the start of a job such as age, gender, race, education, and whether the job is protected by a union. We include unemployment rate at the start of the job, u_0 , to analyze the effect of aggregate labor market conditions when the job is created. We also include the current unemployment rate, u_t , as a time-varying regressor to capture the on-going labor market conditions. We obtain data from the Bureau of Labor Statistics for the national unemployment rate. The time series is not seasonally adjusted so that it is consistent with the data from NLSY.

The NLSY 1979 also provides detailed information about the reason why a job spell ended. A detailed description of the reasons for job terminations is available in the Appendix A. In particular, We observe whether the job ended due to the worker’s quit decision to take or look for another job or due to the firm’s firing decision. The theory predicts that workers and firms response to aggregate labor market conditions are different and the overall effect on the duration of a job spell is ambiguous. On one hand, workers are willing to accept low-paying jobs during recessions due to tight labor market conditions, and perhaps quit later during booms to take or look for a better job. Workers’ incentive to quit for a better job tends to reduce the duration of the job. On the other hand, firms hire among a larger applicant pool during recessions and can potentially wait for high-quality matches that endure longer. This intuition also suggests that the jobs ending in quit (worker-initiated separations) and the jobs ending in firings (firm-initiated separations) can exhibit opposite behavior. This is the main motivation of why we look at the different termination reasons, especially quits and layoffs.

3 Estimation strategy

The Cox (1972) proportional hazard model is widely applied to duration data when time to a failure event is of interest. In the analysis of employment duration, the failure event of interest is the termination of a job. In our analysis, there are multiple causes of job terminations, and only the first of these causes for job termination, if any, is observed. In other words, each reason for job termination is a competing risk for the other reasons. In this section, we describe two alternative approaches proposed in the literature when there are competing risks: cause-specific hazard regressions and regression on a subhazard function.⁶

History Roster (Beta Version). This roster alleviates the more involved linking process across different survey years.

⁶Both methods have their pros and cons—see, for example, Putter, Fiocco and Geskus (2006) for a general discussion.

3.1 Cause-specific hazard functions

Let the hazard function for job terminations be:

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}.$$

The hazard function is the instantaneous probability that a job is terminated at time T conditional on surviving up to time t . Cox (1972) further imposes that the hazard function for job terminations, conditional on a set of explanatory variables at time t , $X(t)$, takes the following proportional form:

$$h(t|X(t)) = h_0(t) \exp(X(t)\beta), \quad (1)$$

where $X(t)$ are time-varying explanatory variables, β is a vector of parameters common across all job spells, and $h_0(t)$ is the baseline hazard. The baseline hazard is also common across all job spells, and its form is left unspecified. Cox (1972) describes a semi-parametric approach for obtaining estimates of the model parameters, $\hat{\beta}$, through the maximization of the following partial likelihood function:

$$\mathcal{L} = \prod_{i:C_i=1} \frac{h(t_i|X_i(t_i))}{\sum_{j:t_j \geq t_i} h(t_i|X_j(t_i))} = \prod_{i:C_i=1} \frac{\exp(X_i(t_i)\beta)}{\sum_{j:t_j \geq t_i} \exp(X_j(t_i)\beta)}, \quad (2)$$

where $C_i = 0$ if the job spell is right-censored. Note that right-censored job spells enter the partial likelihood function only through the denominator. Further, the baseline hazard can be recovered non-parametrically after obtaining $\hat{\beta}$ even though it cancels from the estimating equation. The proportionality assumption implies that the hazard functions are strictly parallel and inference is possible solely based on $\hat{\beta}$. Specifically, a positive (negative) value of $\hat{\beta}$ implies that the probability of terminating a job increases (decreases) with an increase in the value of the explanatory variable.

A standard application of the Cox proportional hazard model can be misleading when there are competing events. The proportional hazard model in equation (1) assumes that the explanatory variables affect the probability of terminating a job in the same way regardless of its cause. However, the model is misspecified under such a restriction if the effect of one of the explanatory variables is different for each cause-specific job termination. In this study, a quit and a firing are competing events for job terminations, and the theory predicts that both the starting and current unemployment rate affect the probability of terminating a job due to quits or firings in opposite directions.

Taking this issue into account, here we define a separate hazard function for each cause-

specific job termination. Formally, let k denote one of the K possible cause of job terminations. The hazard function for terminating a job due to reason k is:

$$h_k(t|X(t)) = h_{0,k}(t) \exp(X(t)\beta_k). \quad (3)$$

The specification in equation (3) is similar to the standard specification in equation (1) except that it is now separately defined for K different possible reasons for job terminations. Both the baseline hazard functions and the parameters are allowed to differ across different types of job terminations. β_k 's can be estimated separately for each cause-specific hazard function by maximizing the partial likelihood function in equation (2). However, the occurrence of a competing event is treated as right-censored in each of these estimations.

3.1.1 Cumulative incidence functions and inference

While the estimation procedure with cause-specific hazard functions is the same as with the standard Cox proportional hazard model without competing risks, the interpretations of the parameter estimates are different. Because the distributions of time to a job termination for each cause-specific event are potentially dependent, the sign of the parameter estimates alone cannot determine the effect of a covariate on the duration of employment. When the hazard functions are estimated separately for each cause-specific job termination, the effect of a change in the variable of interest on a cause-specific job termination depends nonlinearly on baseline hazard functions and parameter estimates of the other cause-specific hazard functions.

To illustrate this point, let the baseline cumulative cause-specific hazard function be

$$H_k(t) = \int_0^t h_k(s)ds.$$

Then, the probability of surviving from any event at time t is

$$S(t) = \exp\left(-\sum_{k=1}^K H_k(t)\right).$$

The survival probability now depends on the baseline and parameter estimates not only from the hazard regression of the event of interest, but also from the hazard regressions of the other competing events. Further, the probability of failing from cause k before time t is:

$$I_k(t) = \int_0^t h_k(s)S(s)ds. \quad (4)$$

The probability in equation (4) is called the *cumulative incidence function*. The cumulative incidence function represents the probability that failure from cause k occurs before time t . Since this is an intuitively appealing object, below we measure the effect of a change in the starting and current unemployment rates on quits and firings by constructing cumulative incidence functions.

3.2 Regression on a subhazard function

As an alternative to cause-specific hazard regressions, Fine and Gray (1999) propose a methodology that allows inference on cumulative incidence functions solely based on estimates of β . They define a subhazard function for the competing risk k as follows:

$$\bar{h}_k(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | T \geq t \cup (T \leq t \cap K \neq k))}{\Delta t}. \quad (5)$$

The subhazard function shows the instantaneous probability of a job ending due to reason k conditional on surviving up to time t or ending before time t due to a reason other than k . Similarly to Cox's proportional hazard model, Fine and Grey (1999) assume that the subhazard function takes the form:

$$\bar{h}_k(t|X(t)) = \bar{h}_{0,k} \exp(X(t)\beta_k). \quad (6)$$

The subdistribution hazard function in equation (6) can be estimated in a way that is analogous to equation (2). The only difference in the estimation procedure is in the treatment of the risk set. According to equation (5), job spells that have already ended due to another cause are still considered to be in the risk set for the competing risk k . Since these observations can potentially become right-censored and dropped from the risk set (but the censoring cannot be observed because job spells have already ended), Fine and Grey (1999) weight them using the Kaplan-Meier estimate of the survivor function for the censoring distribution.

One of the advantages of the estimation strategy proposed by Fine and Grey (1999) is that inference can now be made solely based on $\hat{\beta}$, because the subhazard function is directly linked to the cumulative incidence function. Note that the baseline cumulative incidence function and subhazard function for the competing risk k are related as follows:

$$\text{CIF}_k = 1 - \exp\left(-\int_0^t \bar{h}_k(s)ds\right).$$

The estimates of β have a similar interpretation to the standard Cox proportional hazard model. A positive (negative) value of $\hat{\beta}_k$ implies that the effect of increasing the value of the

explanatory variable increases (decreases) the probability of terminating a job due to cause k .

4 Results

4.1 Sample restrictions

Following Bowlus (1995), we restrict the data set to include only private sector employment. Jobs that start before the individual completes all schooling or is younger than 16 years old are dropped from the sample. Further, jobs with missing job start and stop dates and those lasting less than two weeks are not included in the sample. Unlike Bowlus (1995), we still include females in my sample. Bowlus (1995) restricts the sample to only males on the grounds that females are likely to quit for reasons other than poor match quality, such as marriage, pregnancy, and childcare. The information about the reason for job terminations allows us to distinguish job terminations due to professional concerns from personal concerns. Therefore, we do not need to make such a restriction on our sample.

We define three categories for the reasons of job terminations: quits, firings, and other reasons.⁷ Our interest in quits comes from the intuition that, from workers' perspective, job spells should be shorter for those jobs created during recession because workers are willing to take a low match-quality jobs foreseeing that they will quit to take or look for better jobs. Accordingly, it is natural to categorize quits due to reasons other than to take or look for another job into "other reasons." The firm-side incentives imply longer spells for jobs created during a recession, because these matches are expected to be high quality, and firms are less likely to fire these workers. Thus, the "firings" category includes discharges and layoffs. Termination of temporary and seasonal jobs are included in "other reasons" category, because these jobs are set for a fixed term regardless of match quality. Terminations due to closings are also included in "other reasons" category since all jobs regardless of match quality are terminated with this type of job termination.⁸

The original dataset consists of one observation per job and multiple spells for each individual. If there is an individual-specific unobserved component, the job spells for the same individual are potentially correlated and the estimates of β are biased. To address the concerns about unobserved heterogeneity, we follow Bowlus (1995) and randomly select one spell per individual. Bowlus (1995) argues that such a restriction on the sample produces unbiased estimates of β . However, the estimates for the baseline hazard functions are still

⁷Appendix A presents the full list of NLSY reasons, along with our categorization.

⁸Inclusion of these type of job terminations in the "firings" category does not change the conclusions.

biased, because longer spells are now overrepresented in the sample. Since cumulative incidence functions are constructed from the estimates of the baseline hazard functions, they are also potentially biased. While the bias in cumulative incidence function calculations is problematic for inference from the cause-specific hazard regressions, this is not a concern for the subhazard regressions because inference is possible solely based on the estimates of β .

4.2 Preliminary estimation

As a preliminary step, we first repeat Bowlus (1995) analysis in Appendix B. First we run her estimation with the same time period as hers (from 1979 to 1988) and the same sample restrictions. Despite the retrospective corrections of the samples and randomness in selecting spells, our result is qualitatively very similar to hers. In particular, u_0 has a significantly positive effect on separation probability, indicating that the match quality is higher for the jobs that are created in booms. Then we extend the sample period to the same as the current analysis (from 1979 to 2010) and repeated the analysis. Now the effect of u_0 becomes statistically insignificant. Thus, the total effect is ambiguous. The difference is likely due to the age of samples—Bowlus’ (1995) samples are very young workers, whose labor market experiences are very different from older workers. To the extent that we are interested in the behavior of typical worker-firm match, our samples are more representative of the entire economy than hers. Below, in our main analysis, we show that the effect of u_0 is more transparent once we take the reasons of separations into account.

4.3 Quits, firings, and other reasons

Table 1 presents our main estimation results. The first three columns show the estimation results from the cause-specific hazard regressions for job terminations due to quits, firings, and other reasons, respectively. The last three columns show the results from the subhazard regressions. The coefficients of interest are those for the unemployment rate at the start of the job spell, u_0 , and the current unemployment rate, u_t , for quits and firings.

The effects of the explanatory variables can be directly inferred from the estimates of the subhazard regressions. The effect of u_0 is positive and statistically significant for the job spells ending by a worker’s quit decision to take or look for another job. The positive sign implies that a high unemployment rate at the start of a job spell increases the probability that the worker is more likely to quit his current job. This result is consistent with our intuitions on the worker-side behavior. Regarding the effects of u_0 on job spells ending by firm’s firing decision, the sign of the coefficient from the subhazard regressions supports the predictions of our intuitions on the firm-side behavior. In contrast to the job terminations

Variable	Cause-Specific Hazard			Subhazard		
	Quits	Firings	Other	Quits	Firings	Other
u_0	.157* (.017)	-.052* (.022)	-.134* (.018)	.344* (.021)	-.101* (.030)	-.214* (.024)
u_t	-.104* (.017)	.138* (.020)	.090* (.0166)	-.360* (.024)	.151* (.029)	.116* (.023)
HS	.086 (.063)	-.269* (.068)	-.148* (.054)	.189* (.063)	-.227* (.067)	-.056 .055
COL	.063 (.076)	-1.337* (.129)	-.627* (.078)	.379* (.076)	-1.063* (.129)	-.355* (.078)
AGE	.661* (.046)	.071 (.039)	.024 (.024)	.541* (.045)	-.072* (.033)	-.101* (.022)
SQAGE	-.012* (.000)	-.002* (.001)	-.001* (.000)	-.010* (.000)	.001* (.001)	.001* (.000)
NWHITE	.082 (.043)	.325* (.055)	.061 (.042)	.026 (.043)	.277* (.054)	-.000 (.042)
GEN	-.150* (.041)	-.299* (.056)	.347* (.040)	-.176* (.041)	-.330* (.055)	.408* (.040)
UNION	-.473* (.055)	-.084 (.061)	-.608* (.055)	-.187* (.053)	.267* (.061)	-.374* (.054)
Occurrence:	2522	1416	2542	2522	1416	2542
# of observations: 7655						
# of right-censored observations: 1175						

Table 1: UNION=1 if the job is covered under a union contract or collective bargaining agreement; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses. * indicates significant at 5%

due to quits, the sign of the coefficient for u_0 is negative and statistically significant. The negative coefficient implies that a high employment rate at the start of a job reduces the probability that a firm will fire the worker in the future.

In the aggregate data, the cyclical behavior of aggregate quits and firings are qualitatively different. While quits are strongly pro-cyclical, firings are counter-cyclical. This macro-level observation suggests that workers and firms also respond to u_t in opposite directions. The negative coefficient for u_t from the subhazard regression for quits indicates that the probability that a job spell ends by a worker's quit decision is lower during recessions. In contrast, the coefficient estimate from the subhazard regression for firings is positive and statistically significant. The positive coefficient implies that the probability that a job spell

ends by a firm’s firing decision is higher during a recession. Both of these estimates are consistent with the cyclical behavior of quits and firings.

The results for the effect of u_t are crucial for isolating the effect of u_0 , as the duration of a job spell is affected by the current cyclical fluctuations. Bowlus (1995) and Mustre-del-Rio (2012) both include the unemployment rate as an explanatory variable for the hazard regressions. However, the model suffers from misspecification bias if u_t has opposite effects on the decisions of workers and firms. In both of these papers, the coefficient estimate for u_t is statistically insignificant when it is added linearly to the model. To account for the cyclical patterns in quits and firings, Bowlus (1995) further adds the squared value of u_t to the right-hand side variables, and the estimates for the explanatory variables involving u_t becomes significant. By distinguishing job separations according to their causes, we separately identify the effects of current cyclical fluctuations on the duration of a job spell ended by quits and firings. The opposite signs for quits and firings support the discussion about the effect of u_t raised in Bowlus (1995).

4.3.1 Cumulative incidence functions

While the estimates from the subhazard regressions provide a direct inference on the effects of u_0 and u_t on quits and firings, using these estimates to make inferences about the overall duration of employment can be misleading. The subhazard functions for different reasons of job terminations are estimated separately, and the probability of job termination can potentially exceed one when the value of one of the explanatory variables is changed.⁹

To evaluate the overall behavior of employment duration, we use the coefficient estimates from the cause-specific hazard regressions. Note that the estimates of the coefficients from the cause-specific regressions alone are not informative about the effects of u_0 and u_t , although the signs agree with the estimates from the subhazard regressions. Therefore, we obtain the cumulative incidence functions for each job termination category using the coefficient and baseline hazard estimates from the cause-specific hazard regressions. By construction, the probability of job termination is less than unity at any point in time.

Figure 1 shows the cumulative incidence functions for each cause-specific job terminations. The cumulative incidence functions are drawn for a 29 year-old high-school graduate white male whose job is not protected by a union. The unemployment rate is set equal to the average value of the unemployment rate for the survey years, 6.10%, and it is assumed to be equal to this value for all of the time periods from the start of the job. The plots for all three reasons are stacked so that the differences show the probability of observing the

⁹The probability of ending a job exceeds one after 150 weeks when the starting unemployment rate is one standard deviation above its sample mean.

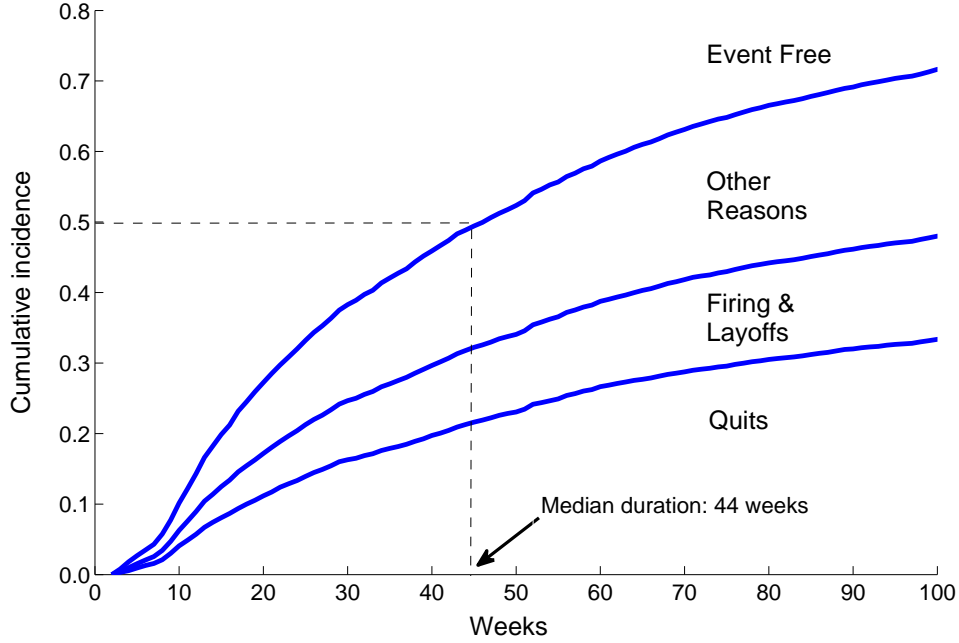


Figure 1: Cumulative incidence functions for quits, firings, and other reasons. The cumulative incidence functions are stacked so that the distance between two curves represents the probabilities of the different events.

corresponding cause-specific job termination before time t . At any time t , the difference between the sum of cumulative incidence functions and one represents the survival probability. Thus, the median duration of a job is 44 weeks.

Figure 2 shows the effects of a change in u_0 on the cumulative incidence functions for quits, firings, and other reasons. In each plot, the solid curves show the cumulative incidence functions when u_0 is equal to its sample mean. The dashed and dotted curves correspond to the cumulative incidence functions when u_0 is one standard deviation, 1.46%, above or below its sample mean. The current unemployment rate is still kept at its average value for all of the remaining time periods.

The cumulative incidence functions constructed from the cause-specific hazard regressions are consistent with the results from the subhazard regressions. When u_0 is equal to its sample mean, the probability of quitting a job is equal to 0.225 at the median employment duration. This probability increases to 0.288 if u_0 is one standard deviation above its sample mean and decreases to 0.173 when u_0 is one standard deviation below. Firings respond to changes in u_0 in the opposite direction. At the median employment duration, the probability of firing a worker decreases from 0.094 to 0.085 when u_0 is one standard deviation above its sample mean. This probability increases to 0.102 when u_0 is one standard deviation about its sample

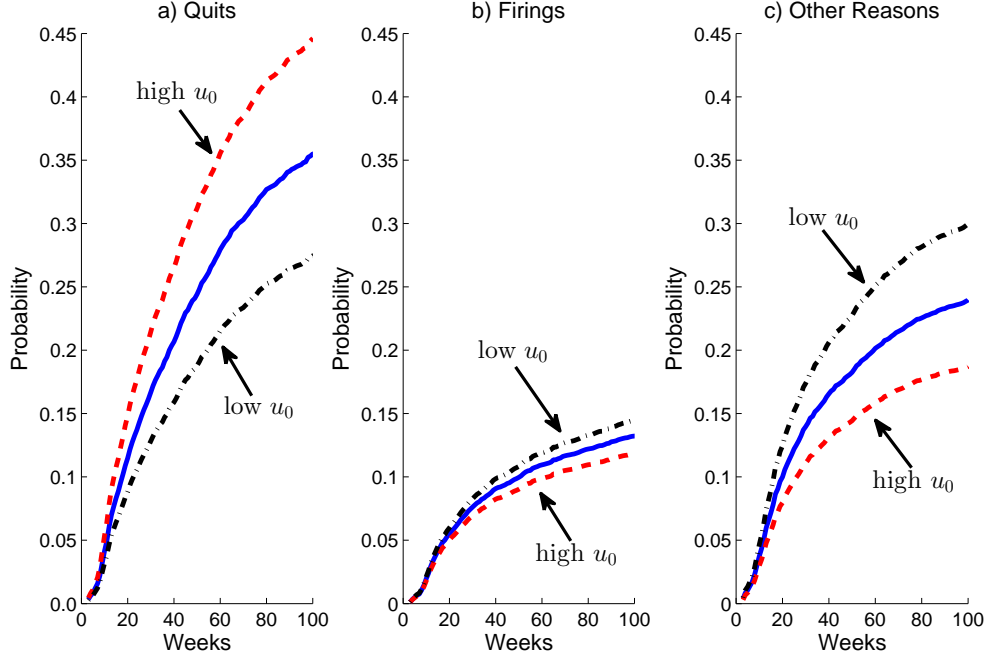


Figure 2: Changes in cumulative incidence functions in response to a change in u_0 .

mean. The behavior of job terminations are similar to those due to firings. At the median employment duration, the probability of terminating a job due to reasons other than quits and firings is equal to 0.173. This probability decreases to 0.137 when u_0 is above its sample mean and increases to 0.215 when u_0 is below its sample mean.

The overall effect of these opposing forces on the duration of a job spell is ambiguous. Taken together with job terminations due to other reasons, the overall effect of u_0 on the duration of employment is negative but small. The duration of employment decreases from 44 weeks to 42 weeks if u_0 is one standard deviation above its sample mean and it increases by only one week when u_0 is one standard deviation below its sample mean. Duration of employment is used as a proxy for match quality in the literature. Therefore, these findings suggest that match quality is weakly pro-cyclical.

Similar results hold for the effects of u_t . Figure 3 shows the change in the cumulative incidence functions for cause-specific job terminations after a change in u_t . In each plot, the solid curves show the cumulative incidence functions when u_t is equal to its sample mean. The dashed and dotted curves correspond to the cumulative incidence functions when u_t is permanently one standard deviation above or below its sample mean for all the periods after the job spell has started.

Changes in u_t affect the cumulative incidence functions constructed from the cause-specific hazard regressions in the same direction implied by the coefficient estimates from the

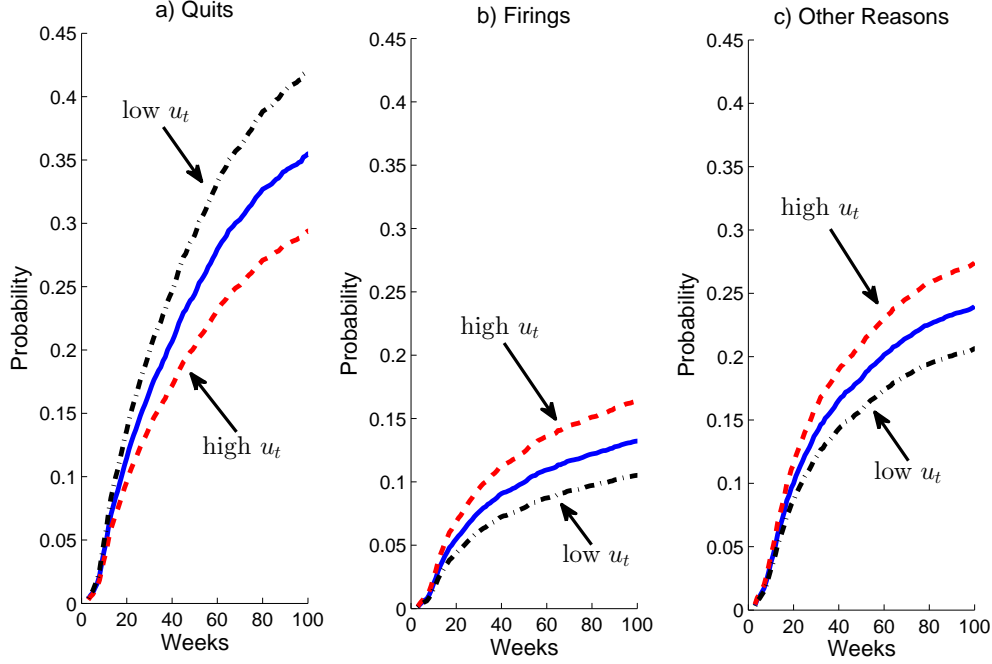


Figure 3: Changes in cumulative incidence functions in response to a change in u_t .

subhazard regressions. At the median employment duration, the probability of quitting a job decreases from 0.225 to 0.187 if u_t is permanently increased by one standard deviation above its sample mean and increases to 0.268 when u_t is permanently one standard deviation below its sample mean. Unlike quits, the probability of being fired increases with u_t as implied by the subhazard regressions. At the median employment duration, the probability of firing a worker increases from 0.094 to 0.116 when u_t is permanently one standard deviation above its sample mean, but it decreases to 0.075 when u_t is permanently one standard deviation below its sample mean. The response of job terminations due to other reasons is similar to the response of firings. At the median employment duration, the probability of terminating a job due to a reason other than quits and firings increases from 0.173 to 0.198 when u_t is permanently above its sample mean, but it decreases to 0.149 when u_t is permanently below its sample mean.

4.4 *EE* and *EU* transitions

While quits and firings are informative about who initiated the job termination, these self-reported job termination reasons can potentially lead to measurement errors. For example, an employee can be forced to quit by being offered a very low wage. Although such an event appears as a quit in the data, this job termination is essentially initiated by the employer.

To address this measurement issue, we create an alternative classification to job terminations in the light of the theoretical model. We classify job terminations according to the labor market status of the employee after the termination of the job. We group the job spells into two categories. If the employee moves to another job within a month after the termination of the job, we classify it as employment-to-employment (*EE*) movement. Otherwise, the job spell is classified as employment-to-non-employment (*EU*) movement. Accordingly, we define two hazard functions, one for job spells ending with an *EE* movement and another one ending with an *EU* movement. This time, we treat movements to another job and non-employed status as competing risks. Then, we apply the same procedure as we did with quits and firings. The estimation results from cause-specific hazard and subhazard functions are in Table 2.

5 Model

In this section, we analyze a simple job-ladder model in order to interpret our empirical finding in a more formal context. Our model focuses on the decision of workers on whether to accept a job with a given match quality. Firms' decisions are not modeled explicitly—one interpretation is that firms' decisions are implicit in the distribution of offered match quality (the distribution is assumed to be the same over time) and labor market frictions. Another interpretation is that the match formation/separation decision is efficient so that the workers' decisions and the firms' decisions agree with each other.

5.1 Setup

The model setup is the standard job-ladder model.¹⁰ An infinitely-lived worker is either employed or unemployed. We assume that his utility is linear, and thus he consumes what he receives each period. An employed worker receives the wage of zx . The component z is the aggregate productivity and x is the match quality. z follows a Markov process according to $F(z'|z)$, where $'$ (prime) represents the next period. We assume that x is constant for a given job. At the beginning of the following period, an employed worker can receive two different shocks. First, he may receive a job offer from another employee. The probability of this shock is $\lambda_e(z') \in [0, 1]$. Note that this probability is a function of the next period aggregate state z' . The match quality of this new job is random and drawn from a distribution that is constant over time, $G(x)$. After seeing the match quality, he chooses whether to stay in the same job, move to the new job, or move to unemployment. Second, he may receive a

¹⁰Moscarini and Postel-Vinay (2014) use a similar model in their analysis of the Great Recession.

	Cause-Specific Hazard		Subhazard	
Variable	<i>EE</i>	<i>EU</i>	<i>EE</i>	<i>EU</i>
u_0	.048* (.014)	-.027 (.016)	.118* (.017)	-.049* (.022)
u_t	-.032* (.014)	.092* (.015)	-.158* (.020)	.081* (.022)
HS	.051 (.050)	-.277* (.050)	.188* (.051)	-.267* (.050)
COL	.151* (.064)	-1.041* (.083)	.281* (.062)	-.876* (.081)
AGE	.310* (.025)	.108* (.024)	.206* (.023)	-.032 (.023)
SQAGE	-.005* (.000)	-.002* (.000)	-.004* (.000)	-.000 (.000)
NWHITE	-.017 (.036)	.338* (.039)	-.141* (.035)	.355* (.039)
GEN	-.281* (.034)	.299* (.038)	-.386* (.034)	.480* (.039)
UNION	-.490* (.045)	-.360* (.050)	-.203* (.043)	-.172* (.047)
Occurrence:	3605	2756	3605	2756
# of observations: 7598				
# of right-censored observations: 1237				

Table 2: Estimation Results for Hazard Functions under *EE* and *EU* Classification: UNION=1 if the job is covered under a union contract or collective bargaining agreement; GEN=1 if the respondent is female; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses. * indicates significant at 5%

separation shock with probability $\delta(z') \in [0, 1]$ which forces him to move to unemployment. We assume that $\lambda_e(z') + \delta(z') \leq 1$ for all z' .

An employed worker's Bellman equation can be written as

$$\begin{aligned}
W(x, z) = & zx + \beta E_{x', z'} [\lambda_e(z') \max\{W(x', z'), W(x, z'), U(z')\} \\
& + (1 - \lambda_e(z') - \delta(z')) \max\{W(x, z'), U(z')\} + \delta(z') U(z')].
\end{aligned}$$

Here, $W(x, z)$ is the value function of an employed worker, $U(z)$ is the value function of an unemployed worker, and β is the discount factor.

An unemployed worker receives a job offer with probability $\lambda_u(z') \in [0, 1]$. After observing the match quality of the offer, he chooses whether to take that job. An unemployed worker's Bellman equation is therefore

$$U(z) = b + \beta E_{x', z'} [\lambda_u(z') \max\{W(x', z'), U(z')\} + (1 - \lambda_u(z'))U(z')].$$

5.2 Calibration

One period is set as a month. The discount factor is set at $\beta = 0.99^{\frac{1}{3}}$, as in Gertler and Trigari (2009). Following Hall and Milgrom (2008), we choose b so that it is 0.71 of the average wage. $F(z'|z)$ approximates an AR(1) process:

$$\log(z_{t+1}) = \rho_z \log(z_t) + \epsilon_t,$$

where $\epsilon_t \sim N(0, \sigma_z^2)$. We set $\rho_z = 0.95^{\frac{1}{3}}$, again following Gertler and Trigari (2009). For σ_z , we target the cyclicalty of the wages of new hires. This is because it is commonly considered that the existing workers' wages tend to be sticky, and here what affects the match formation is the wages at the time of contact between the worker and the firm. Shimer (2005) estimates that the standard deviation of labor productivity is 2% quarterly, after HP-filtering with parameter 10⁵. In Pissarides (2009), the elasticity of job changers' wages with respect to labor productivity is estimated to be 1.70. Haefke et al. (2013) estimates this elasticity to be 1.31 for new hires from non-employment and 2.02 for job changers, although the standard errors are large (Table 8). This provides the target of the quarterly standard deviation of wages for new match to be from 2.6% to 4.0%. We set σ_z to be 0.01, which gives us 3.1% value for this target.

The logarithm of the match quality shock is normally distributed with its mean normalized to zero, $\log(x) \sim N(0, \sigma_x^2)$. The dispersion in x directly affects the gains from switching to another employer. Tjaden and Wellschmied (2014) estimates the average wage gain upon job-to-job transition to be 3.3%, and we target this value. This gives us $\sigma_x = 0.035$.

The labor market frictions, $\lambda_u(z)$, $\lambda_e(z)$, and $\sigma(z)$, are calibrated using labor market flows. First, we assume that $\lambda_e(z)$ is proportional to $\lambda_u(z)$; $\lambda_e(z) = \alpha \lambda_u(z)$.¹¹ We set $\alpha = 0.27$ to target average job-to-job flow rate of 1.4% per month, again taken from Tjaden and Wellschmied (2014).

We assume that $\lambda_u(z)$ and $\delta(z)$ takes the following form:

$$\lambda_u(z) = \bar{\lambda}_u + \phi_\lambda \log(z)$$

¹¹Mukoyama (2014) discusses the validity of this assumption.

Parameter	Description	Target/Source	Value
β	Discount Factor	Gertler and Trigari (2009)	$0.99^{\frac{1}{3}}$
b	Value of unemployment	Hall and Milgrom (2008)	0.735
ρ_z	Persistence of aggregate shocks	Gertler and Trigari (2009)	$0.95^{\frac{1}{3}}$
σ_z	Dispersion of aggregate shocks	cyclicality of new hire's wages	0.01
σ_x	Dispersion of match quality	Tjaden and Wellschmied (2014)	0.035
α	$\lambda_e(z)$ relative to $\lambda_u(z)$	Tjaden and Wellschmied (2014)	0.27
$\bar{\lambda}_u$	Average value of λ_u	Krusell et al. (2015)	0.242
$\bar{\delta}$	Average value of δ	Krusell et al. (2015)	0.014
ϕ_λ	Fluctuation parameter of λ_u	Krusell et al. (2015)	1.10
ϕ_δ	Fluctuation parameter of δ	Krusell et al. (2015)	0.063

Table 3: Calibration

and

$$\delta(z) = \bar{\delta} - \phi_\delta \log(z).$$

The average values, $\bar{\lambda}_u$ and $\bar{\delta}$, are set so that the model replicates the gross flow rate for unemployment to employment and employment to unemployment. Krusell et al. (2015) calculates these values (with adjustments to measurement errors) as 0.235 and 0.014. The parameter values are $\bar{\lambda}_u = 0.242$ and $\bar{\delta} = 0.014$. The parameters governing the fluctuations, ϕ_λ and ϕ_δ , are set so that the fluctuations of the corresponding flow rates in the model mimics the behavior of the data. Krusell et al. (2015) calculates the standard deviation of (quarterly averaged, logged, and HP-filtered with parameter 1600) these flows as 0.085 and 0.085. We obtain $\phi_\lambda = 1.10$ and $\phi_\delta = 0.063$. Table 3 summarizes the calibration.

5.3 Results

The model implies the steady-state value of unemployment at 5.6%. The standard deviation of (for all summary statistics below, the variables are quarterly averaged, logged, and HP-filtered with parameter 1600) employment and unemployment rate are 0.009 and 0.136. The corresponding empirical values are 0.010 and 0.113 in the data. As in the data, the flow rate for job-to-job transition and UE flow are procyclical and EU flow rate is countercyclical (the corresponding correlation coefficients with unemployment rate are -0.686 , -0.876 , and 0.821). Thus the model represents the aggregate cyclical movement of the labor market very well.

Now we turn to the micro-level behavior of employment duration. Table 4 presents the

	Cause-Specific Hazard		Subhazard	
Variable	EE	EU	EE	EU
u_0	.051*** (.002)	−.005* (.002)	.074*** (.003)	−.085*** (.003)
u_t	−.084*** (.002)	.090*** (.002)	−.141*** (.003)	.161*** (.003)
Occurrence:	95741	93014	95741	93014
# of observations: 188755				

Table 4: Regression results from model generated data. Standard errors are given in parentheses. * indicates significant at 5%, ** indicates significant at 1%, and *** indicates significant at 0.1%

result of running the same estimation as Section 4 on model-generated data. The model predictions are largely consistent with the empirical result.

5.3.1 Intuitions

Interpreting the coefficients for u_t is straightforward. Largely because of the movements in $\lambda_e(z)$ and $\delta(z)$, EE flow is procyclical and EU flow is countercyclical. Interpreting the coefficients on u_0 requires more information, as it is a reflection of quality of the matches formed in the past.

The key to understanding these coefficients is what type of matches are created at each point in time. Figure 4 plots the workers who transits from U to E , and Figure 5 plots the workers who transits from another job. It can be seen that the first type of workers on average have a higher quality when the unemployment rate is high. Figure 5 exhibits an opposite pattern.

Because the distribution of x that a new worker draws from is constant over time, the difference in the average x in Figure 4 has to come from the difference in the reservation match quality (the value of x above which the worker accepts the match) of workers. In fact, the pattern of reservation match quality can be seen from Figure 6.

There are two properties that are notable in Figure 6. First, the reservation match quality is decreasing in z . This means that the “very bottom” jobs are created in booms, and they are destroyed when recession arrives. This is reflected in the (small but) negative entry of u_0 ’s influence on EU flow, although the mapping between the match quality and the coefficient is not exact because of the competing risks structure. The jobs that are created in booms are more likely to be separated into U . Second, the slope is very small, compared

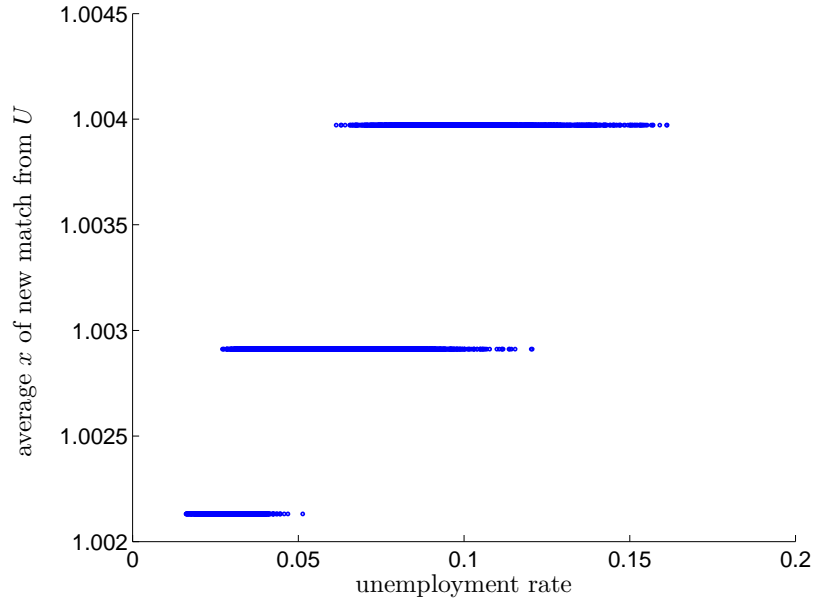


Figure 4: Average value of new x for UE transition against the unemployment rate

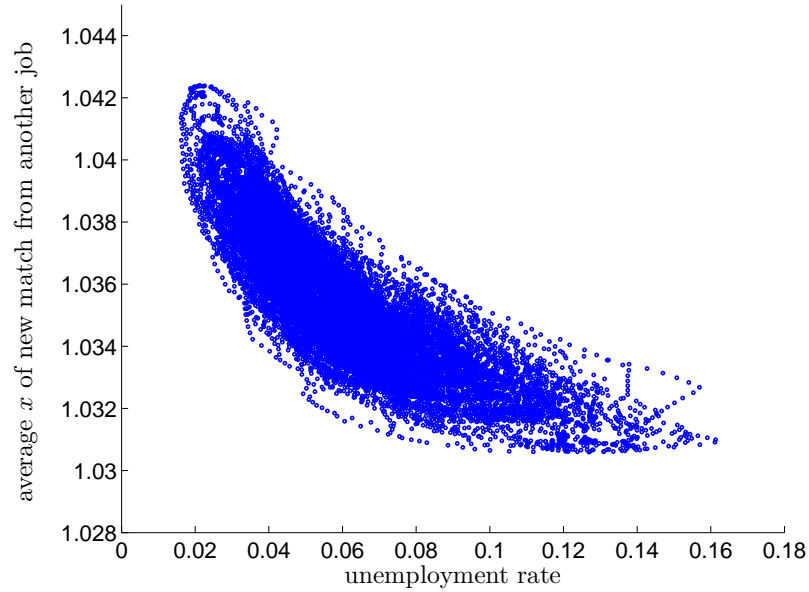


Figure 5: Average value of new x for EE transition against the unemployment rate

to the fluctuations in z . This is because there are multiple effects offsetting each other. First and the most obvious effect is that when z is high, zx can be high even if x is low, so that an even low x can be accepted. Second, because $\lambda_u(z)$ is increasing in z , there are more chances of obtaining another draw in booms, and this makes the worker more choosy during

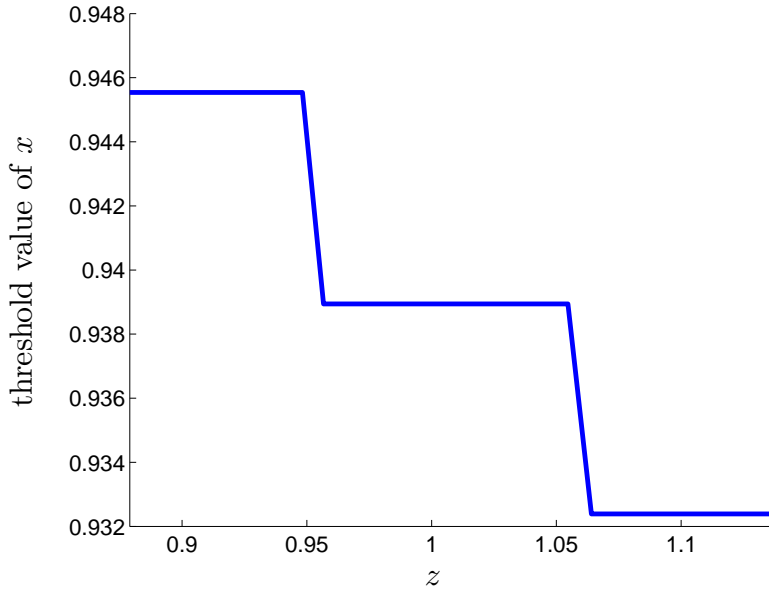


Figure 6: Reservation match quality for each x

booms. This raises the reservation match quality in booms—the exact opposite of the first effect. The third effect is that because $\lambda_e(z)$ is increasing in z , the worker is willing to take a low- x match, thinking that there will soon be another chance on the job. This offsets (a part of) the second motive of waiting in booms.

The fact that the profile in 6 is close to flat implies that these effects are almost exactly offsetting each other. This is reflected in the small size in the coefficient on u_0 for EU transition (although, once again, the mapping is not exact because of the competing risks structure). It is almost statistically insignificant despite that we generate a very large number of sample. We believe that this is in fact a favorable property of the model, considering that the corresponding coefficient in Table 2 is insignificant.

It is straightforward to understand the relationship in Figure 5. In booms, the average match quality is already better, because of the more frequent opportunity for job-to-job transitions (this can be seen from Figure 7 which plots the overall match quality). Thus the new match formed by a job-to-job transition should have a higher match quality than recessions. The pattern in Figure 5 is reflected in the coefficient on u_0 for EE in Table 4. Because the average x of jobs created in recessions by job-to-job transitions are of worse quality, these jobs will have more opportunity to experience EE transition in future.

In sum, the model provides intuition for our empirical results in earlier sections, without trying to directly interpret the coefficients. It is a lot easier to interpret what is going on in the model, since we can observe the match quality there.

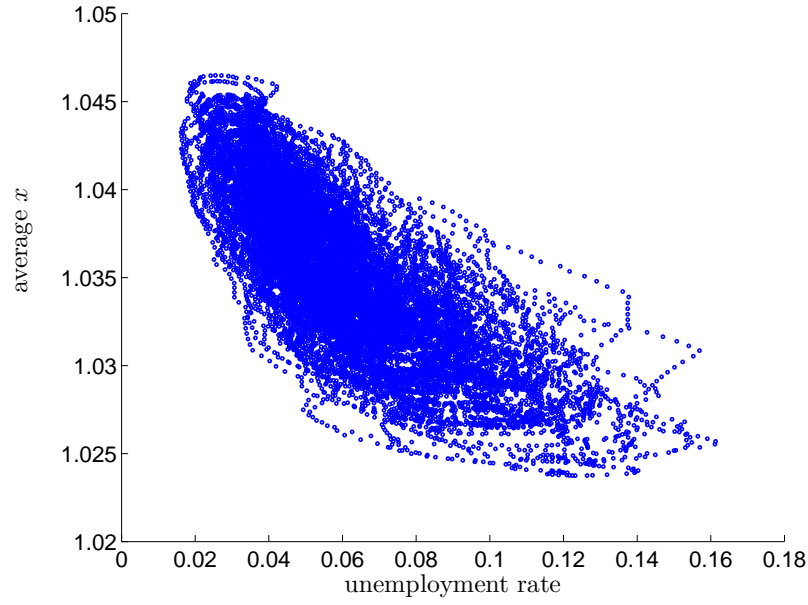


Figure 7: Average value of x against the unemployment rate

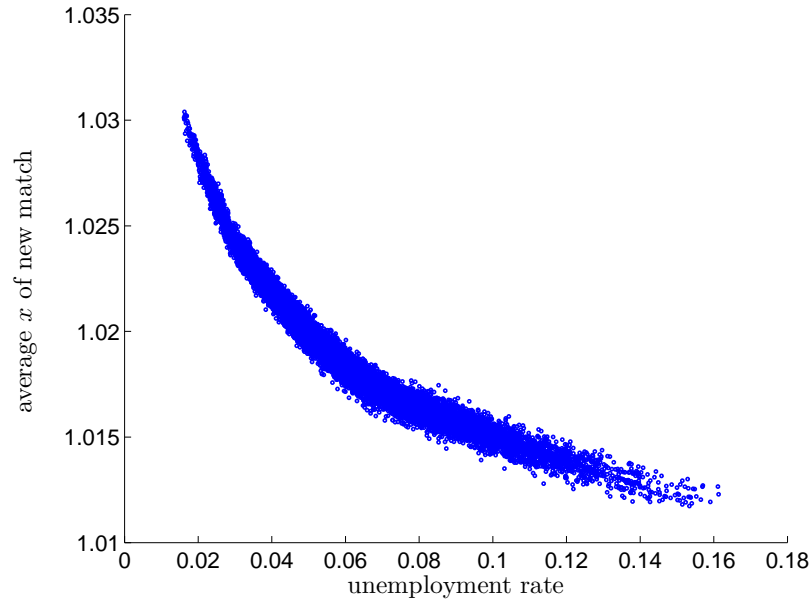


Figure 8: Average value of x for newly formed match against the unemployment rate

Finally, going back to the original question of whether a better quality match is created during booms or recessions, we can provide two answers. First, because the offered match quality distributions in the job-ladder model is acyclical and it is still capable of generating the regression coefficients that are empirically relevant, we can conclude that the cyclical

of offered match quality distribution is not necessary in explaining the pattern of employment duration. This is important because one possible explanation of Bowlus' (1995) result is a technology shock that is cohort-specific.¹² Second, the change in job-to-job transition is an essential driver of the quality distribution of new matches over the business cycle. In this sense, Bowlus' (1995) takeaway that the quality of new matches is procyclical survives (Figure 8 plots the overall average quality of new matches), despite the fact that the coefficient on u_0 for her Cox (1972) regression in our extended samples is not statistically different from zero. We reached this conclusion from an entirely different route—by separating different types of separations and building a model that matches the data very well.

6 Conclusion

In this paper, we empirically examined the effects of labor market conditions on the duration of employment. Using data from NLSY 1979 cohort, we estimate a proportional hazard model under the assumption that different causes of job terminations are competing risks. we use information about the reason why a job spell has ended to distinguish job terminations due to quit from firing. Making a distinction between different types of separations is the main contribution of this paper, because it allows us to test separately for *both* of these opposing forces rather than estimating their *net* effect on the duration of employment. We have also examined the distinction between job-to-job transitions and transitions into unemployment.

Two methods have been widely used in the literature to estimate hazard models when there are competing risks. we apply both of these methods in this paper and they produce results that are consistent with each other. We find that an increase in the unemployment rate at the start of an employment relation increases the probability that the worker quits his job to take or look for another job, but it reduces the probability that the firm fires the worker. The net effect of these opposing forces on the duration of employment is negative. Previous papers in the literature using the NLSY 1979 cohort also find a negative effect, but we find this effect to be much smaller. When the unemployment rate at the start of the employment relationship is one standard deviation above its sample mean, the median duration of a non-union job held by a 29 year-old white male with a high school degree decreases from 44 weeks to 42 weeks. These results suggest that match quality is weakly pro-cyclical.

The distinction between job-to-job transitions and transitions into unemployment yielded a similar result. This was expected because majority of quits results in job-to-job transitions

¹²See, for example, Costain and Reiter (2008).

and fired workers tend to transit into unemployment.

There can be several different interpretations for the different patterns of quits and firings. In order to examine the mechanism formally, we built a simple job-ladder model and calibrated it to the U.S. data. The model outcome is consistent with the empirical results.

The model allows us to interpret the results in the empirical part more directly in the context of match quality. The model outcome shows that the job-to-job transition plays an important role in analyzing the time-series in the average quality of new matches. Our result suggest that in asking the questions of “mismatch,” it is essential to take the job-to-job transition into account.

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Appendix

A List of termination reasons

Categorization follows [Q]-quit, [F]-firing, and [O]-other reasons.

1. Layoff, job eliminated [F]
2. Company, office or workplace closed [O]
3. End of temporary or seasonal job [O]
4. Discharged or fired [F]
5. Government program ended [O]
6. Quit for pregnancy, childbirth or adoption of a child [O]
7. Quit to look for another job [Q]
8. Quit to take another job [Q]
9. Other (SPECIFY) [O]
10. Quit because of ill health, disability, or medical problems [O]
11. Moved to another geographic area [O]
12. Quit to spend time with or take care of children, spouse, parents, or other family members [O]
13. Quit because didn't like job, boss, coworkers, pay or benefits [O]
14. Quit to attend school or training [O]
15. Went to jail, prison, had legal problems [O]
16. Transportation problems [O]
17. Retired [O]
18. No desirable assignments available [O]
19. Job assigned through a temp agency or a contract firm became permanent [O]

- 20. Dissatisfied with job matching service [O]
- 21. Project completed or job ended [O]
- 22. Business failed or bankruptcy [O]
- 23. Sold business to another person or firm [O]
- 24. Business temporarily inactive [O]
- 25. Closed business down or dissolved partnership [O]

B Replicating Bowlus (1995)

Here we replicate Bowlus (1995) for our samples.

B.1 Sample period 1979-1988

Table 5 uses the same time period as Bowlus (1995). It can be seen that the results are quite similar to each other. In particular, u_0 has positive and significant effect on the separation probability.

B.2 Sample period 1979-2010

Now we extend the period to 2010. We still maintain the same sample restrictions as Bowlus (1995). Table 6 presents the results. Some of the results change noticeably. In particular, the coefficient on u_0 is now not significantly different from zero. This is consistent with the small overall effect of u_0 in our analysis in the main text.

C Computational details of the model

[To be completed]

Variable	Bowlus	Our samples
u_0	.050 (.023)	.060 (.016)
u_t	-.460 (.183)	-.321 (.125)
u_t^2	.028 (.011)	.018 (.008)
HS	-.260 (.066)	-.148 (.044)
COL	-.521 (.106)	-.837 (.081)
AGE	-.152 (.112)	.082 (.086)
SQAGE	-.003 (.003)	-.002 (.002)
NWHITE	.090 (.068)	.079 (.039)
UNION	-.174 (.076)	-.472 (.047)
Occurrence:	2135	4330

Table 5: UNION=1 if the job is covered under a union contract or collective bargaining agreement; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses.

Variable	Bowlus	Our samples
u_0	.050 (.023)	−.000 (.014)
u_t	−.460 (.183)	.536 (.098)
u_t^2	.028 (.011)	.033 (.006)
HS	−.260 (.066)	−.024 (.045)
COL	−.521 (.106)	−.471 (.066)
AGE	−.152 (.112)	.244 (.025)
SQAGE	−.003 (.003)	−.005 (.000)
NWHITE	.090 (.068)	.129 (.035)
UNION	−.174 (.076)	−.440 (.044)
Occurrence:	2135	4093

Table 6: UNION=1 if the job is covered under a union contract or collective bargaining agreement; NWHITE=1 if the respondent is black or hispanic; SQAGE=age squared; HS=1 if the respondent is a high school graduate, and COL=1 if he completed 16 or more years of education. Standard errors are given in parentheses.